Feature Engineering

Feature engineering is the process of creating new features from existing ones or transforming existing features to improve the performance of a machine learning model. It involves selecting, modifying, or creating features to enhance the model's ability to learn patterns from the data. Effective feature engineering can lead to better model performance, faster training times, and improved interpretability.

Feature Engineering

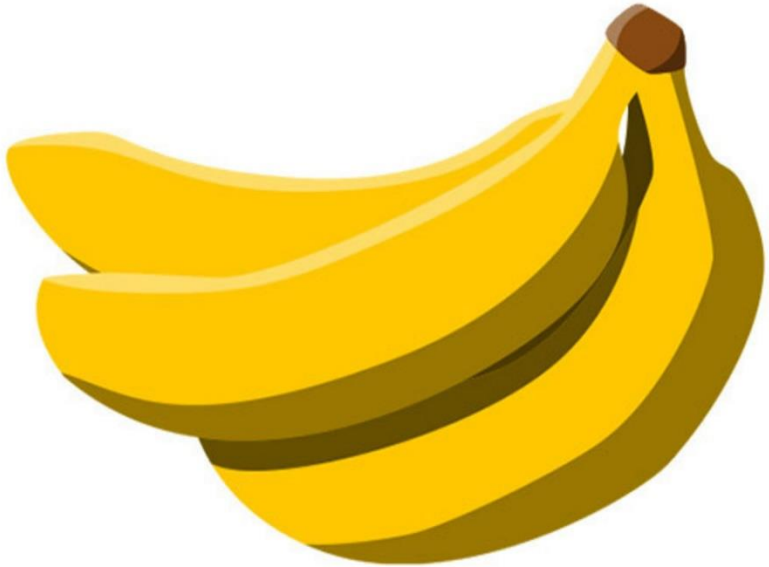
Feature engineering involves manipulating, selecting, or creating features (input variables) from raw data to improve model performance.

- **Transformation:** It includes transforming data through extraction, scaling, and other techniques to help models capture patterns and relationships.
- **Selection:** Choosing relevant features improves model simplicity, interpretability, and generalization by reducing noise and redundancy.
- **Creation:** New features can be engineered to capture important relationships or patterns not apparent in the original data.
- **Missing Data:** Handling missing values through techniques like imputation maintains data integrity.
- **Categorical Variables:** Encoding categorical variables as numerical values enables their use in machine learning algorithms.

Feature Engineering

- **Interaction Features:** Combining existing features to capture interactions between variables can enhance model performance.
- **Domain Expertise:** Feature engineering often requires domain knowledge to make informed decisions about creating meaningful features.
- **Impact:** Effective feature engineering can significantly enhance model accuracy and robustness.
- **Experimentation:** Iterative experimentation with different feature engineering techniques is key to finding optimal features for a given problem and dataset.

Feature Transformation



Feature Transformation

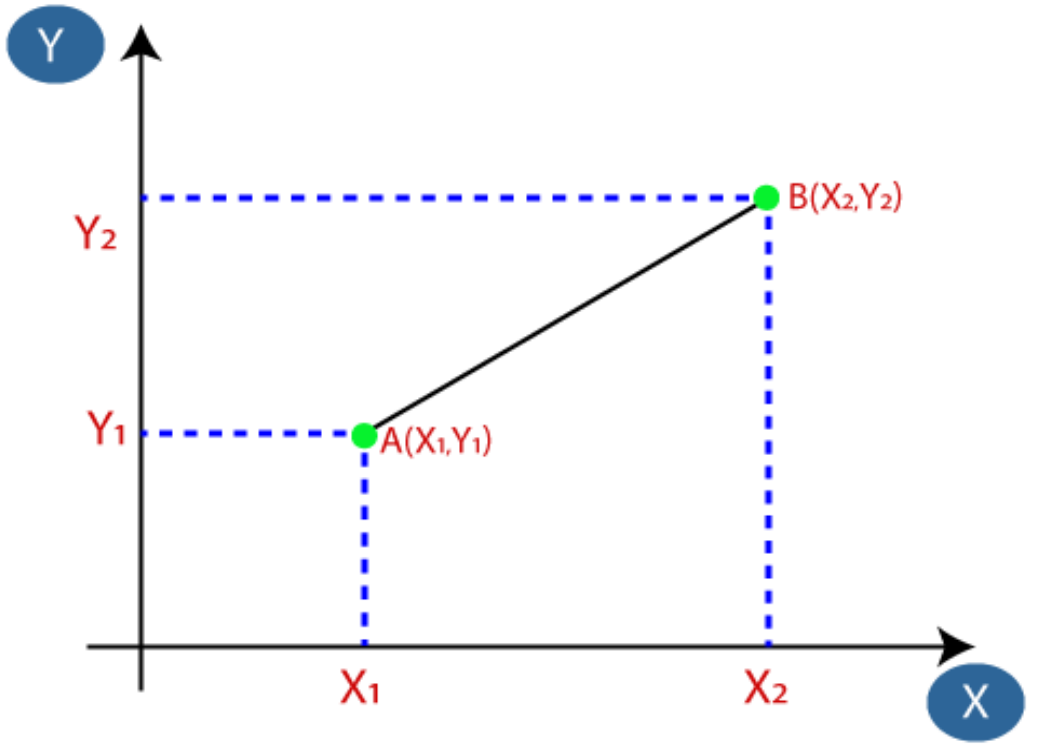
Transformation: It includes transforming data through extraction, scaling, and other techniques to help models capture patterns and relationships.

	cost	transform_cost
0	100	0.333333
1	200	0.666667
2	150	0.500000
3	300	1.000000
4	180	0.600000

Fig: transform data

Feature Transformation

The Euclidean Distance between two points is calculated using a simple formula.



Euclidean Distance between A_1 and $B_2 = \sqrt{(X_2-X_1)^2+(Y_2-Y_1)^2}$

Feature Transformation

The Manhattan Distance between two points is calculated using a simple formula.

Manhattan Distance = $|x_1 - x_2| + |y_1 - y_2|$

Manhattan Distance = $d(x, y) = \sum_{i=1}^{n} |x_i - y_i|$

A few advantages of **feature scaling** the data are as follows:

- ❖ It makes your training faster.
- ❖ It prevents you from getting stuck in local optima.
- ❖ It gives you a better error surface shape.

However, there are few algorithms such as Tree-based algorithms and probability-based algo. that are not affected by the scaling of input data.

Feature Transformation

- **Tree-Based Models:** Feature scaling has minimal impact on models like Random Forests and Gradient Boosted Trees.
- **Neural Networks with Batch Normalization:** Modern neural networks can adapt to feature scales during training, especially with batch normalization.
- **Sparse Models:** Feature scaling may not significantly affect models designed for sparse data.
- **Models Robust to Outliers:** Robust models are less sensitive to the scale of features.
- **Ordinal or Count Data:** Features representing ordinal or count data may not need standardization.
- **Sparse Data with Feature Interactions:** Feature scaling may have limited influence when predictive power relies on feature interactions.
- **Feature Engineering Adequacy:** Additional feature transformations may not significantly improve model performance if existing features capture patterns effectively.

Feature Transformation

Examples of Algorithms where Feature Scaling matters:

- **K-Means** uses the Euclidean distance measure here to feature scaling matters.
- **K-Nearest – Neighbours** also require feature scaling.
- **Principal Component Analysis (PCA)**: Tries to get the feature with maximum variance, here feature scaling is required.
- **Normalization for Gradient Descent:** In optimization algorithms like gradient descent, feature scaling and normalization can significantly impact convergence speed.

Note: Naïve Bayes, Decision Tree, Random Forest & and All tree-based models are not affected by feature scaling.

Techniques to perform Feature Transformation:

- Normalization
- Standardization
- Log Transformation
- Robust Scaler
- Max Absolute Scaler

Feature Transformation

	Student	CGPA	Salary '000
0	1	3.0	60
1	2	3.0	40
2	3	4.0	40
3	4	4.5	50
4	5	4.2	52

Normalization: $X_{new} = \frac{X_i - \min(X)}{\max(x) - \min(X)}$

Python Implementation:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
```

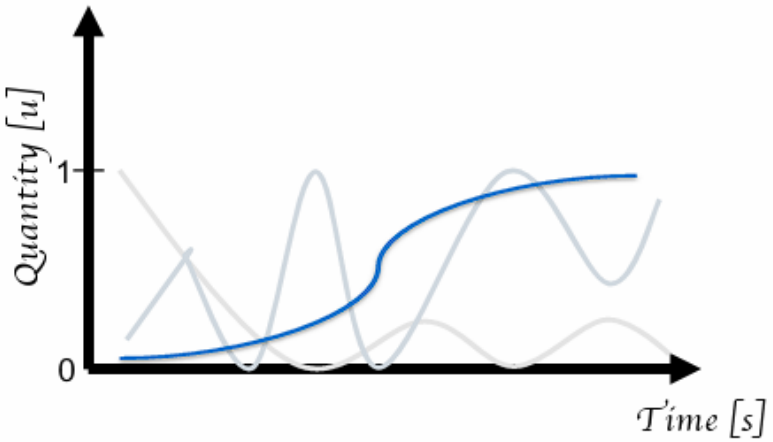
Feature Transformation

Min-Max normalization is defined by:

$$s'_{ij} = \frac{s_{ij} - s_{\min,j}}{s_{\max,j} - s_{\min,j}}$$

where $s_{\max,j}$ and $s_{\min,j}$ are the max and min values of $\boldsymbol{S_j}$.

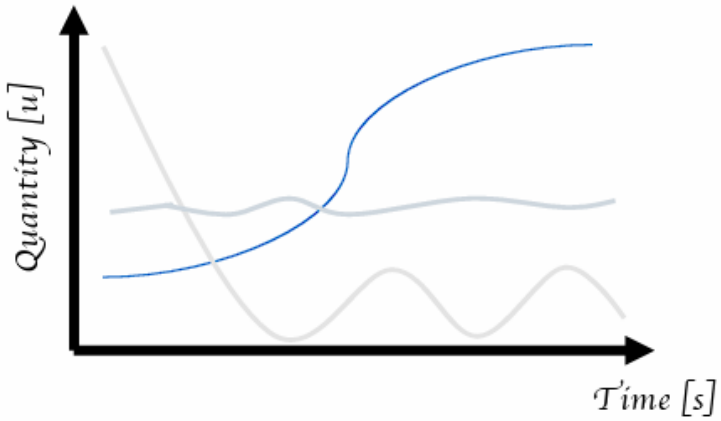
This normalization establish two boundaries for the data between 0 and 1.



Feature Transformation

Let $S = (s_1, \dots, s_T)$ be a multivariate time series, $s_i \in \mathbb{R}^d$ is a d-dimenstional observation at time t_i.

We denote with $\boldsymbol{S_j = (s_{1j}, \dots, s_{Tj})}$ the j-th feature of the time series S, where $s_{ij} \in \mathbb{R}$ is an observation of the j-th feature at time t_i.



Mean normalization is defined by:

$$s'_{ij} = \frac{s_{ij} - \mu_j}{s_{max,j} - s_{min,j}}$$

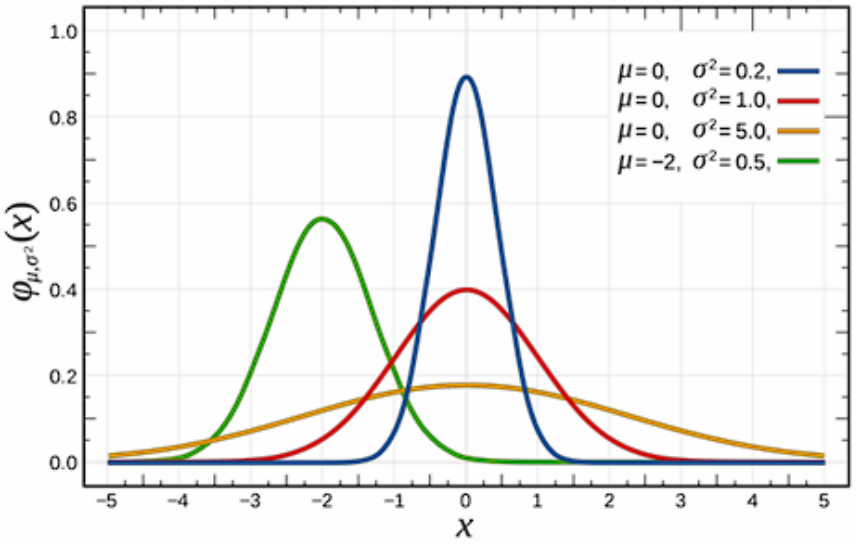
where $s_{max,j}$ and $s_{min,j}$ are the max and min values of $\boldsymbol{S_j}$,

and $\mu_j = \frac{1}{T}\sum_{i=1}^{T} s_{ij}$.

Feature Transformation

Standardization is the process of converting a random variable with mean μ and standard deviation $\boldsymbol{\sigma}$ to a **"standard distribution"** (i.e., zero mean and unit standard deviation).

The **standard score** is the number of standard deviations by which the value of a raw score (i.e., an observed value or data point) is above or below the mean value of what is being observed or measured.



https://en.wikipedia.org/wiki/Normal_distribution

Feature Transformation

	Student	CGPA	Salary '000
0	1	3.0	60
1	2	3.0	40
2	3	4.0	40
3	4	4.5	50
4	5	4.2	52

Standardization: $X_{new} = \frac{X_i - X_{mean}}{\text{Standard Deviation}}$

Standard Deviation: $\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{N}}$

σ = population standard deviation

N = the size of the population

x_i = each value from the population

μ = the population mean

Python Implementation:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

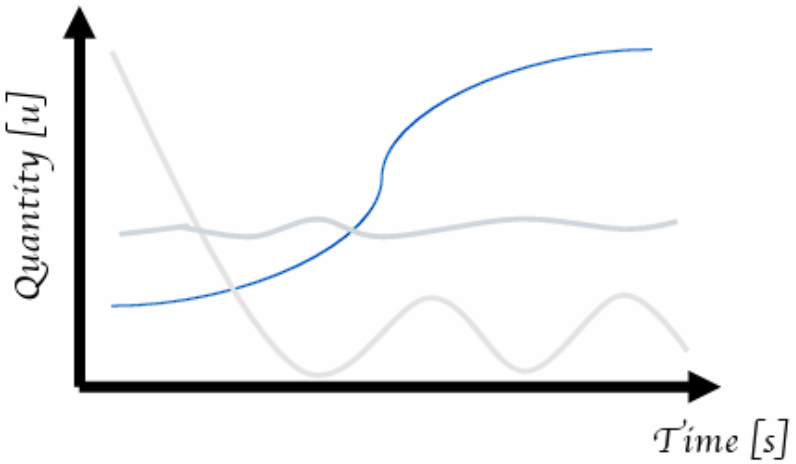
Feature Transformation

Z-score standardization is defined by:

$$s'_{ij} = \frac{s_{ij} - \mu_j}{\sigma_j}$$

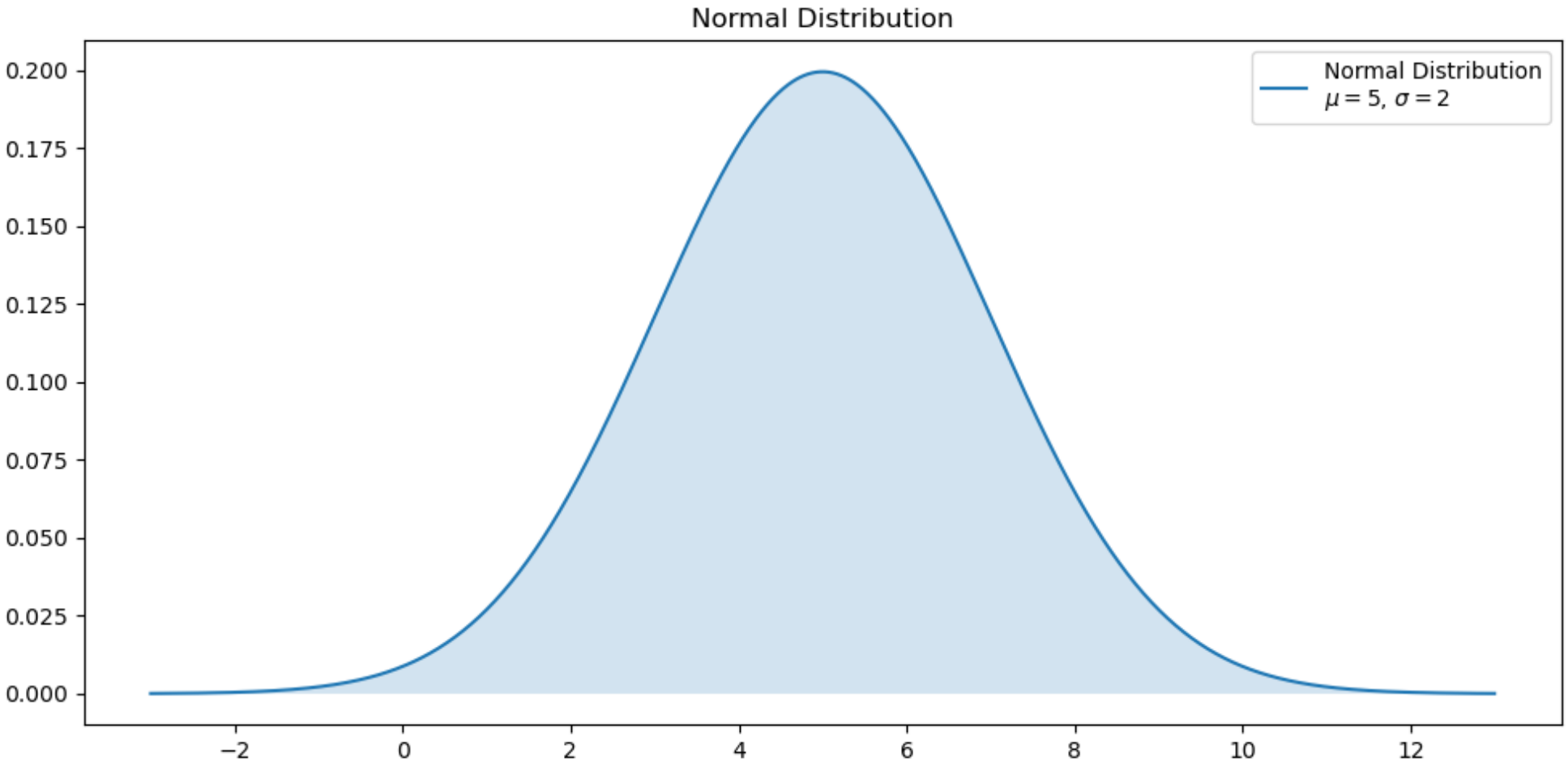
where $s_{max,j}$ and $s_{min,j}$ are the max and min values of S_j, and μ_j and σ_j are the feature mean and standard deviation.

- The transformed data will have zero mean and unit standard deviation.
- It is empirically shown that, if the original distribution is Gaussian, z-score based transformation generates values that are in the range $(-3, 3)$.



Statistical Data Distribution

Normal



The PDF does represent the **data density** at each point along the distribution, and it typically follows a continuous curve. The probability density function (PDF) of the Normal Distribution or Gaussian Distribution, is given by the following equation:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Where:

x is any given value of the variable,

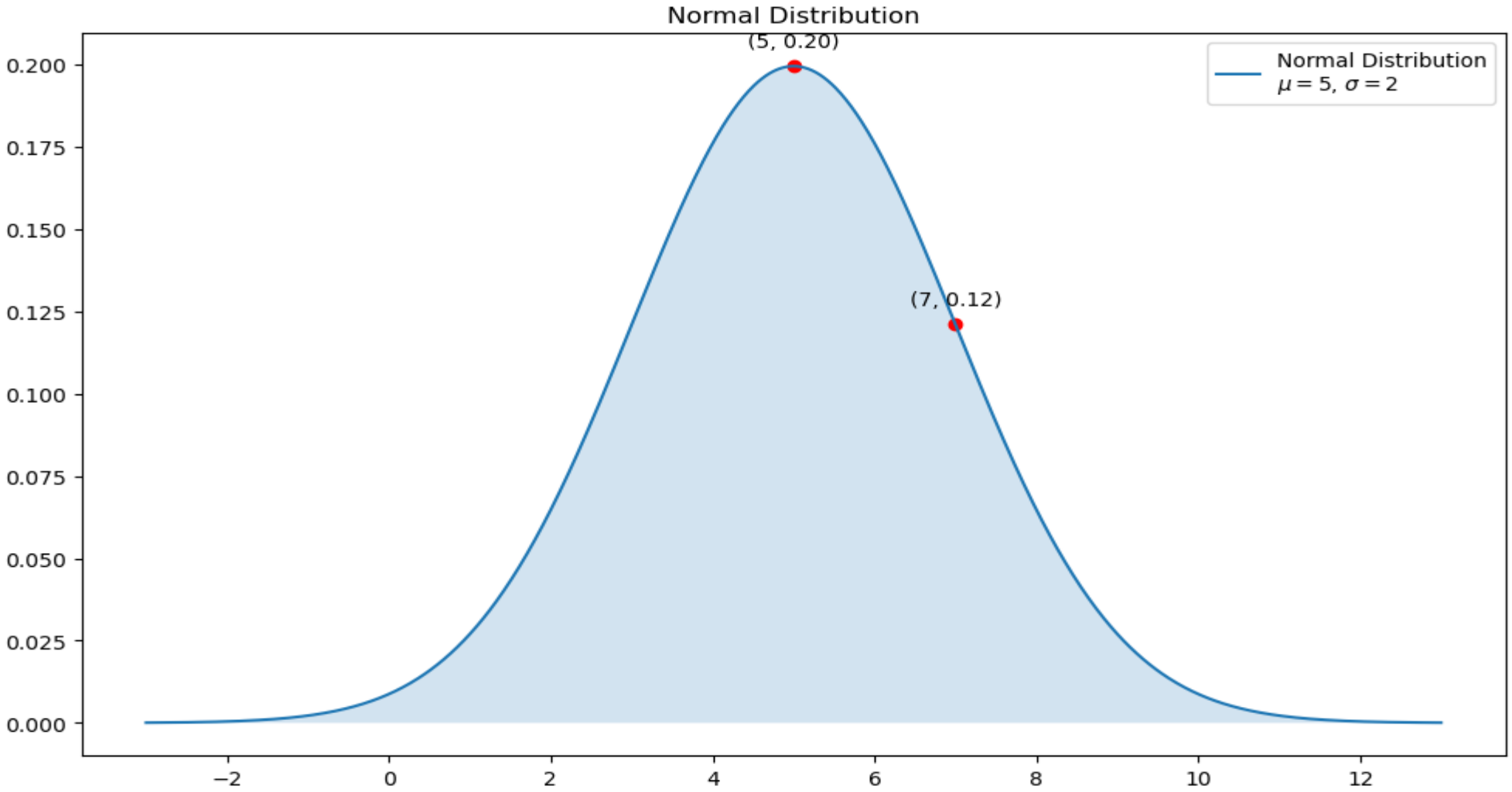
μ is the mean of the distribution,

σ is the standard deviation of the distribution, and

π is the mathematical constant pi (approximately 3.14159).

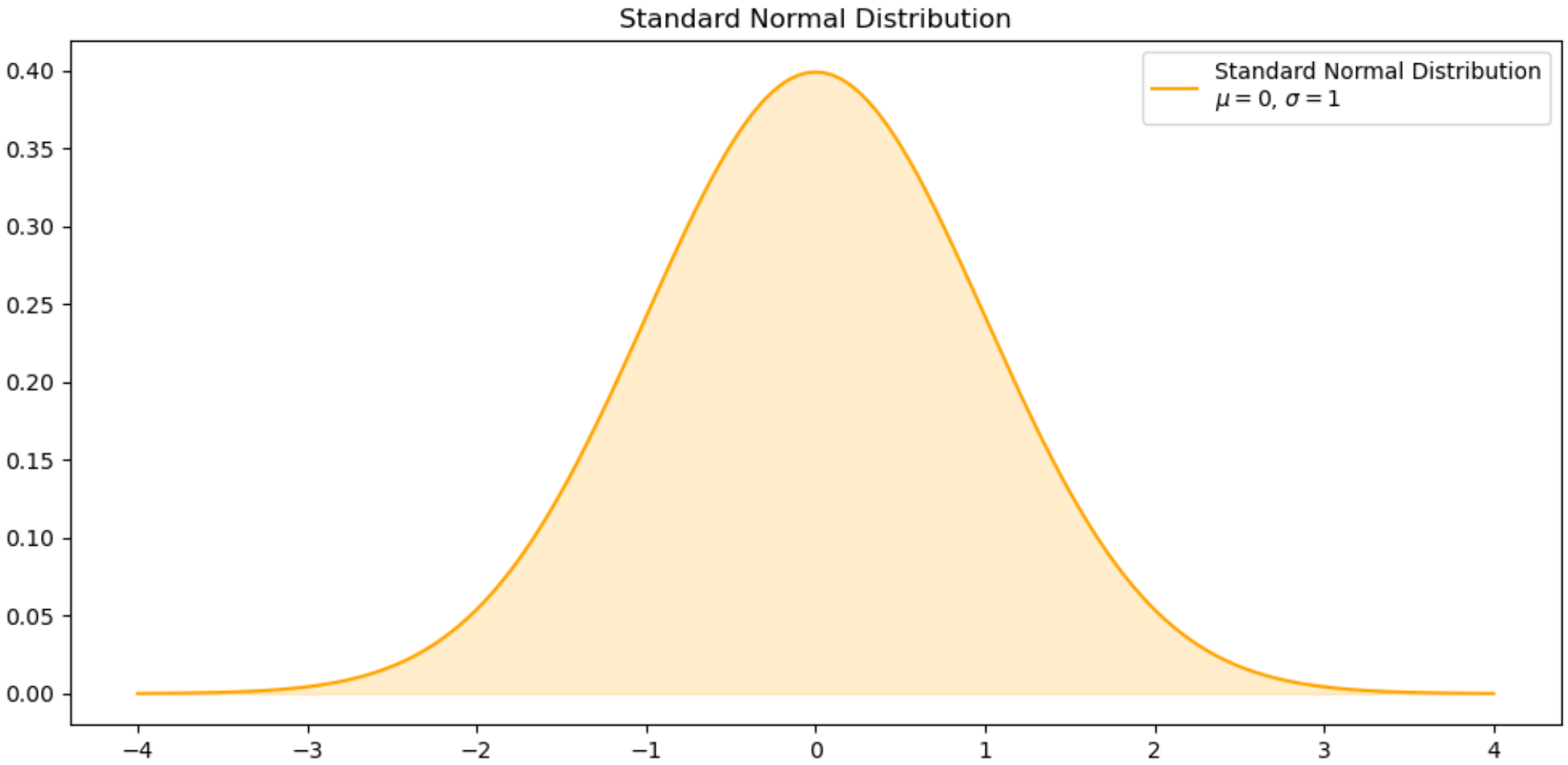
Statistical Data Distribution

Normal



Statistical Data Distribution

Standard Normal

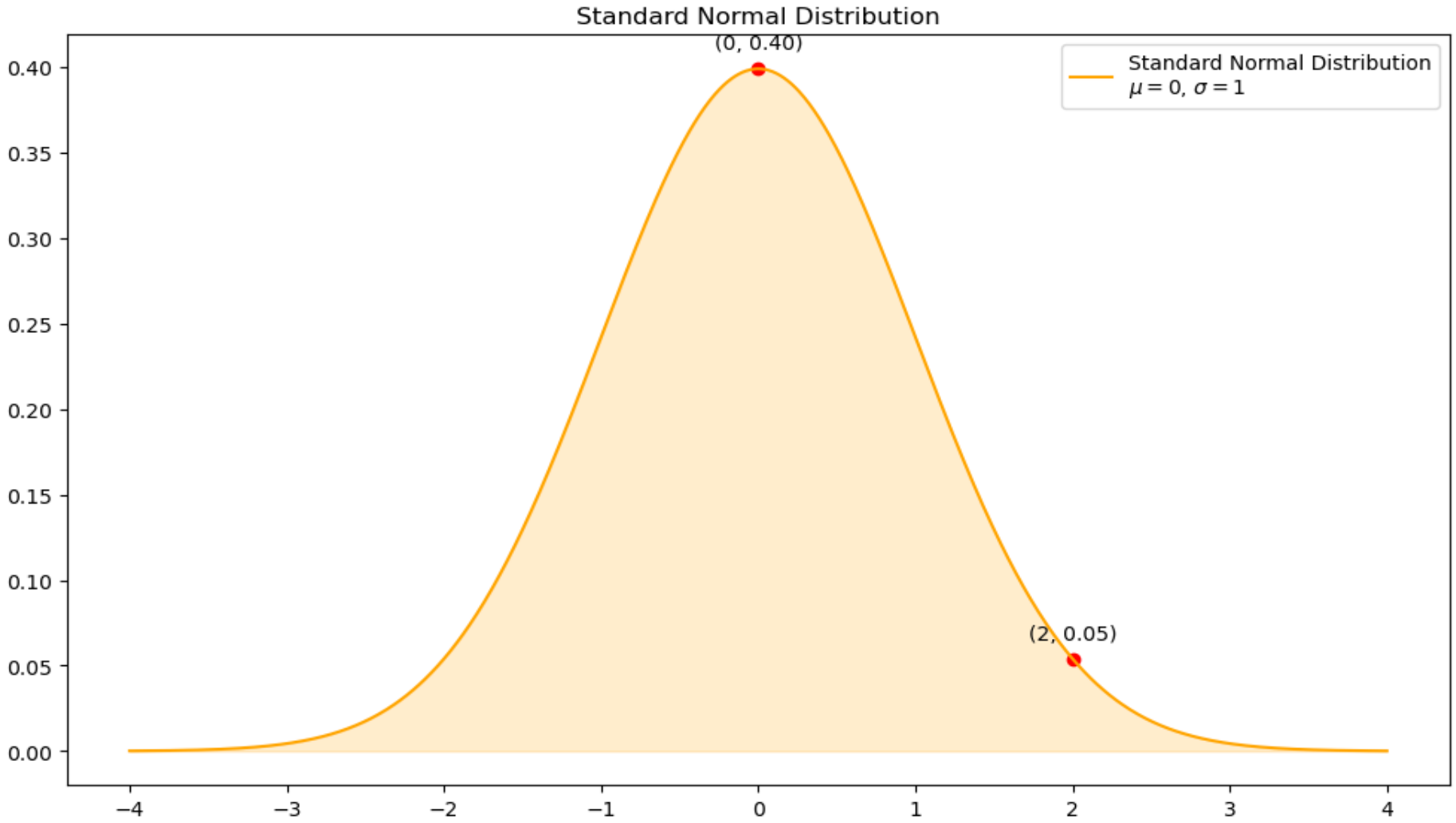


It is the probability density function (PDF) of the standard normal distribution, which describes the likelihood of observing a particular value x in the Standard Normal Distribution. Where, mean=0, and Std=1.

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

Statistical Data Distribution

Standard Normal



1. Standardization (StandardScaler):

1. Standardization is useful when the features in your data have varying scales or different units of measurement.
2. It helps in situations where the distribution of the data does not follow a normal distribution.
3. It is **less affected by outliers** compared to normalization.
4. Standardization preserves the shape of the **original distribution**. It means that when you standardize a dataset, the overall pattern, shape, and distribution of the data points remain the same. The standardized data will have a mean of 0 and a standard deviation of 1, but the relative positions of data points are maintained.

2. Normalization (Min-Max Scaling):

1. Normalization is helpful when the distribution of your **data is not Gaussian** or when you're working with features that have a bounded range.
2. It's particularly useful when you need your features to be on a **specific scale**, such as between 0 and 1.
3. Normalization can be **more sensitive to outliers**, especially when the range is predefined.

Feature Transformation

The **log transform** can be applied as follows:

1. Check if the feature has any zero or negative values. If so, consider using a modified version of the log transform (e.g., adding a constant value or using the logarithm of the absolute values).

2. Add a small constant value (e.g., 5) to the feature before applying the logarithm. This is done to avoid taking the logarithm of zero or close-to-zero values, which would result in undefined or infinite values.

3. Apply the natural logarithm function (base e) to each value of the feature.

Note: When dealing with skewed data distributions or when the relationship between variables is multiplicative rather than additive. https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.FunctionTransformer.html

Robust Scaler are robust to outliers. It is used to scale the feature to median and quantiles Scaling using median and quantiles consists of subtracting the median to all the observations, and then dividing by the interquartile difference. The interquartile difference is the difference between the 75th and 25th quantile:

$$X_{\text{scale}} = \frac{x_i - x_{\text{med}}}{x_{75} - x_{25}}$$

- IQR = 75th quantile - 25th quantile
- RobustScaler= (Xi – X.Median)/IQR

Python Implementation:

```
from sklearn.preprocessing import RobustScaler
RoSc=RobustScaler()
```

Video: https://youtu.be/U9N-ELpCpc8

In simplest terms, the Max Absolute Scaler takes the absolute maximum value of each column and divides each value in the column by the maximum value.

Formula: $$xscaled = \frac{x}{max(x)}$$

Python Implementation:

```
from sklearn.preprocessing import MaxAbsScaler
scaler = MaxAbsScaler()
```

Let’s do it with PYTHON